

Automatic biomechanical graph matching CT-CBCT fusion

Jaime Garcia Guevara, Igor Peterlik, Marie-Odile Berger and Stephane Cotin
Inria France, Université de Lorraine

Image-guided hepatic surgery is progressively becoming a standard for certain interventions. However, limited dose radiation requirements result in lower quality images, making it difficult to localize tumors and other structures of interest. In this paper we propose an automatic registration method exploiting the matching of the vascular trees, visible in both pre and intra-operative images. The graphs are automatically matched using an algorithm combining a Gaussian Process Regression and biomechanical model. This process is automatic, does not require any initialization and handles large intra-operative deformations.

1 INTRODUCTION

Cone-Beam Computed Tomography (CBCT) is an imaging technique in which the X-ray tube and detector panel rotate around the patient, making it easier to deploy in an operating room. While its use is rapidly evolving, it suffers from limited image quality. As a consequence, certain lesions are not visible in CBCT images. This problem can be addressed by fusing intra-operative images with pre-operative data in order to compensate for their lack of detail.

Research in image fusion can be split in two main categories: image-based and feature-based methods [8]. Image-based methods take advantage of the intensity on the whole images. However they are sensitive to the definition of an appropriate similarity metric and they are highly dependent on initial conditions. In feature-based methods, registration is determined from a set of sparse corresponding features. Such methods tend to be less accurate away from the features. In either case, a model of deformation is needed to extrapolate the displacement field computed at the feature level to the entire organ. Such deformation models do not usually ensure that the deformation is physically coherent with the organ biomechanics.

The central idea of our paper is to use a biomechanical model in combination with a vessel graph matching method to compute physically plausible elastic registration of the pre- and intra-operative images of a vascularized organ.

2 Method

The core of our method consists in extracting the vascular tree from both the pre and intra-operative images, and then automatically match the associated graphs. A biomechanical model of the liver is then used to extrapolate the displacement field over the entire organ.

2.1 Extraction of vascular graphs

The vascular tree is segmented in both the pre-operative CT and the intra-operative CBCT images using pipeline that combines the methods described in [7] and [10]. The segmented images are converted to topologies composed of nodes and edges organized to a tree using center-line extraction. We employ an algorithm based on Dijkstra minimum cost spanning tree originally presented in [9] and extended in [4]. The liver parenchyma is segmented from the pre-operative CT using ITKSnap.

2.2 GPR-based vessel graph matching

Our graph matching algorithm is based on [6]. It does not require initialization and handles partial matching as well as topological differences. The method relies on *Gaussian process regression* (GPR) which is a non-parametric kernel-based probabilistic model used to compute a smooth geometrical mapping[5]. In the initial phase, the algorithm iteratively constructs a set of hypotheses where one hypothesis corresponds to a set of matched bifurcations in the source and target graphs. Each hypothesis chosen by the matching process is associated with a quality measure which is the normalized number of *inliers*, i.e. the proportion of mapped source graph points close to the target graph. However the hypothesis selection of this algorithm is not reliable enough for the intra-operative data large deformation we need to handle. Therefore we improved it by recomputing the number *inliers* metric using the biomechanical model (described in section 2.3) transformation to select the best hypothesis.

2.3 Simulating soft tissue deformations

In order to improve the graph matching algorithm as well as to perform the augmentation of the intra-operative view, we

chose to rely on a biomechanical model of the organ, able to handle large deformations and computationally very efficient. We follow the approach of [3] for creating a patient-specific representation, based on a co-rotational linear elastic formulation. The model requires the finite element mesh of the organ of interest. In the actual scenario, we employ a mesh composed of linear tetrahedra which is generated using the method presented in [1] directly from the binary mask of the liver. For both the graph-matching and augmentation, the deformations imposed are modeled by prescribed displacements of points: let us suppose that the actual point s_i located inside the volume of the liver should be displaced to a new position t_i . First, the position s_i is mapped to its embedding tetrahedra via barycentric mapping which remains constant during the deformation. Then, the FE model is deformed using the vector $(t_i - s_i)$ as the prescribed displacement of the mapped position s_i which is imposed to the model via penalty method.

3 Experiments and results

We applied our method to one swine dataset with large deformations due to different pose, pneumoperitoneum and laparoscopic surgical manipulation. The Fig. 1 shows the intra-operative CBCT image, where the vascular tree is not clearly visible. Then the tree and the preoperative model is augmented in Fig. 2.

Three inserted landmarks, up to 7.61 cm distant from bifurcations, were used to compute the target registration error (TRE). Our method achieve a mean TRE of 7.64 mm with 4.24 mm standard deviation. We compared it to the GPR matching [6], that results in mean TRE 13.7 mm with 6.67 mm standard deviation. The GPR deformation and matching becomes unreliable with large deformation and few matching features far from interest landmarks, the common intra-operative scenario. The Fig. 3 depicts this scenario and results.

One human liver deformation was simulated using Hyper-elastic Saint VenantKirchhoff model. Perpendicular pressure forces were applied on most of the liver surface, to produce a deformation similar to the one in [2]. The deformed vessel bifurcations have a 6.27 mm mean, 5.77 mm standard deviation, 22.4 maximum displacement. To resemble CBCT vessels segmentation target graph leafs were randomly removed until only 60% of original bifurcations remained and 2 mm random noise was added. A coarse volumetric mesh with 1328 evenly distributed nodes, that cover the entire liver, was deformed and used to compute the TRE. Our method achieved TRE of 5.38 mm with 3.67 mm standard deviation. While the GPR matching [6] results are mean TRE 18.0 mm with 11.1 mm standard deviation.

4 Discussion and conclusion

We have demonstrated that the use of a (bio)mechanical model noticeable improves the evaluation of the matching hypotheses. The computed deformation of the liver outside the registered domain has a good accuracy, leading the way

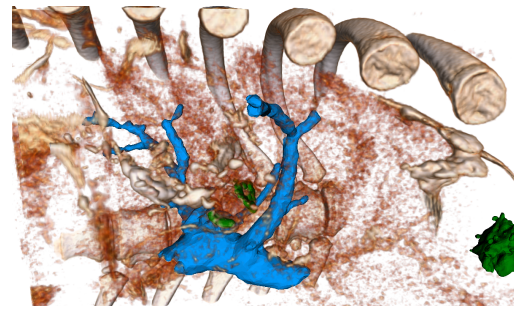


Figure 1: Intra-operative CBCT. Vessels are difficult to identify. The inserted landmarks are in green

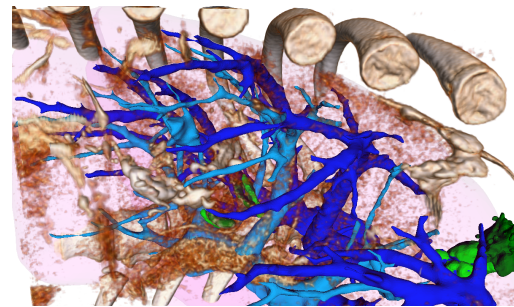


Figure 2: Augmented CBCT, showing clearly the vascular tree (in blue) and the target and registered landmarks (in dark and light green respectively).

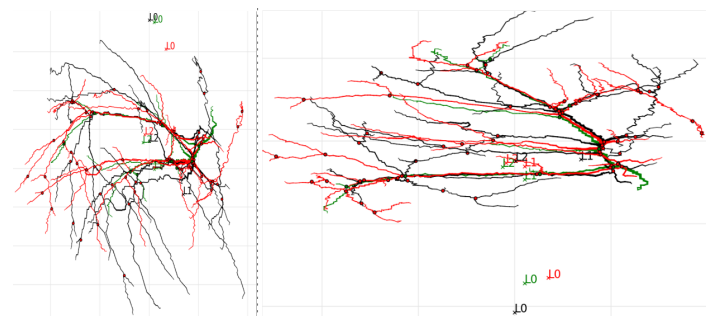


Figure 3: Axial and sagittal view of the registered graphs. The target graph is in green. The registered graphs using the GPR and the biomechanical model are plotted in black and red, respectively. Similarly the evaluation landmarks centroids.

to a useful tool for clinicians. Using the visible liver surface may probably help us to increase the global accuracy in the near future.

References

- [1] Boltcheva, D., Yvinec, M., Boissonnat, J.D.: Mesh generation from 3d multi-material images. In: Proc. MICCAI, pp. 283–290 (2009)
- [2] Nimura, Y., Qu, J.D., Hayashi, Y., Oda, M., Kitasaka, T., Hashizume, M., Misawa, K., Mori, K.: Pneumoperitoneum simulation based on mass-spring-damper models for laparoscopic surgical planning

- [3] Peterlík, I., Duriez, C., Cotin, S.: Modeling and real-time simulation of a vascularized liver tissue. In: Proc. MICCAI. pp. 50–57 (2012)
- [4] Plantefève, R., Peterlik, I., Haouchine, N., Cotin, S.: Patient-specific biomechanical modeling for guidance during minimally-invasive hepatic surgery. *Annals of biomedical engineering* 44(1), 139–153 (2016)
- [5] Rasmussen, C., Williams, C.: *Gaussian Processes for Machine Learning* (2006)
- [6] Serradell, E., Pinheiro, M.A., Sznitman, R., Kybic, J., Moreno-Noguer, F., Fua, P.: Non-rigid graph registration using active testing search. *IEEE Trans. Pattern Analysis and Machine Int.* 37(3), 625–638 (2015)
- [7] Smistad, E., Elster, A.C., Lindseth, F.: GPU accelerated segmentation and centerline extraction of tubular structures from medical images. *International Journal of Computer Assisted Radiology and Surgery* 9(4), 561–575 (2014)
- [8] Sotiras, A., Davatzikos, C., Paragios, N.: Deformable medical image registration: A survey. *Medical Imaging, IEEE Transactions on* 32(7), 1153–1190 (2013)
- [9] Verscheure, L., Peyrodie, L., Dewalle, A.S., Reyns, N., Betrouni, N., Mordon, S., Vermandel, M.: Three-dimensional skeletonization and symbolic description in vascular imaging: preliminary results. *Int J Comput Assist Radiol Surg* 8(2), 233–246 (2013)
- [10] Yushkevich, P.A., Piven, J., Cody Hazlett, H., Gimpel Smith, R., Ho, S., Gee, J.C., Gerig, G.: User-guided 3D active contour segmentation of anatomical structures: Significantly improved efficiency and reliability. *Neuroimage* 31(3), 1116–1128 (2006)